

# Performance Modeling Tools for Parallel Sparse Linear Algebra Computations

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#### **Motivation**



- Parallel sparse matrix algorithms are needed in many large scale computational codes
- Why need accurate performance modeling / prediction tools?
  - Large design space of parallelization strategies
  - Can't afford to implement all algorithm choices
  - Performance depends on machines and input (sparsity pattern)

#### Goals

- 1. Predict performance of existing implementations on emerging architectures
- 2. Design and prototype new algorithms, eliminate bad algorithm choices

## **Sparse matrix algorithms**



- Characterization of the workload
  - CPU-bound, memory-bound, or mixture
- Matrix-vector multiplication, triangular solve
  - Purely memory-bound : matrix is read once, flops-tomemory ratio is O(1)
  - Can develop analytical cost models based solely on cache miss count s [Vuduc et al.]
- Factorizations (LU, Cholesky, QR, . . .)
  - Dense is CPU-bound: flops-to-memory ratio is O(N)
  - Sparse is a mixture of CPU-bound and memory-bound:
     Factors are sparser in the beginning, and denser later
  - Analytical cost models are inaccurate [Ashcraft, Grigori et al.]

## **Performance modeling methods**



- Synthetic benchmarks: measure raw performance of the machine's individual components
  - PMTools, STREAM, MultiMAPS, IMB (Intel MPI Benchmarks)
- Analytical cost models
- Trace-based analysis : collect application attributes / addresses during execution, input to cache simulator
  - Can only analyze codes that are memory-bound
- Simulation-framework is more flexible and suitable for predicting performance
  - Write simulation code to mimic application's algorithm, advance simulation time by costs of memory access, operations, and communication
  - Not to worry implementation details (e.g., sparse data structures)

#### **Outline**



- Performance Modeling Tools (PMTools)
  - Calibrate speed of machine's individual components
- Application-specific simulations
  - Validate parallel sparse LU in SuperLU\_DIST
  - Prototype parallel sparse Cholesky

#### **PMTools**

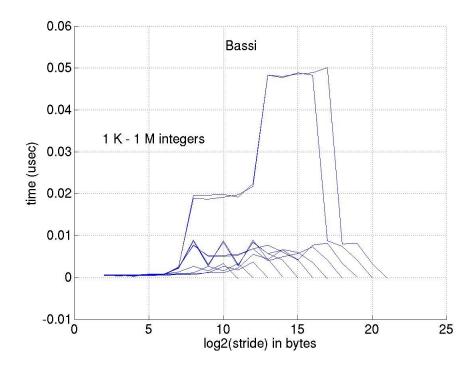


- Micro-benchmarks run off-line, times of basic operations are taken over a parameter space of interest, stored in tables. The omitted values are estimated using interpolation, extrapolation, or curve-fitting
  - Memory: timing memory updates with varying strides
  - BLAS: timing BLAS calls with typical dimensions
  - interconnect: timing point-to-point latency & bandwidth
- Cache simulator, with multiple levels
  - Maintains the state of the memory hierarchy at any time for each processor
  - Estimates the cost of each memory access

### **Memory micro-benchmark**



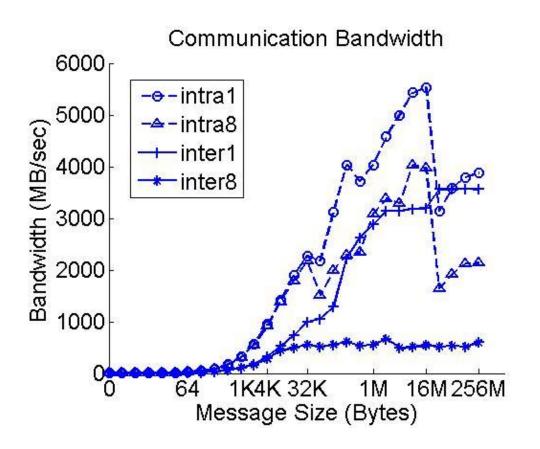
- Measure latency & bandwidth of memory hierarchy
  - Bandwidth: timing sequential updates
  - Latency: timing strided updates [Saavedra]
    - Repeated read/write N elements of a 1D array with stride s, plot the running time as a function of (N, s).
- IBM Power5: L1 (32 KB), L2 (1.92 MB)



#### **MPI** micro-benchmark

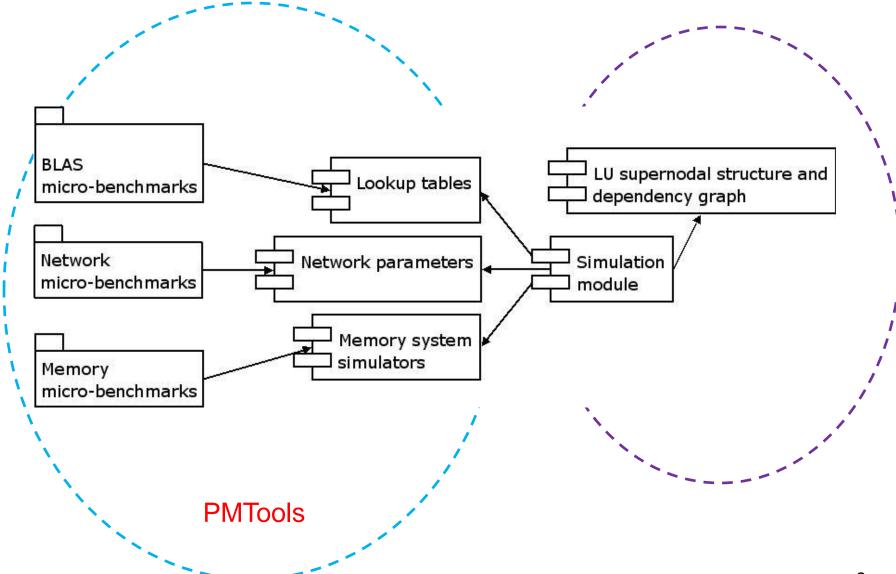


- Ping-pongs between a pair of processors, all pairs, intra-node, inter-node
- Bandwidth on IBM Power5: SMP node, 8 CPUs / node



# **Putting together**

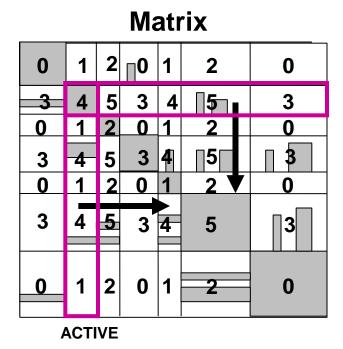




## **Application simulation: sparse LU**



- SuperLU\_DIST [Li/Demmel/Grigori]
- Right-looking relatively more WRITEs than READs
- 2D block cyclic layout
- One step look-ahead to overlap comm. & comp.



#### **Process mesh**

0	1	2
3	4	5

### Simulating update of the k-th block row



```
For all block b in UBLOCKS(k) do

p ← OWNER(b)

time[p] += memory_read (p, b)

for all colomn j in b do

if col j not empty then

time[p] += lookup (dtrsv, sizeof(j))

endif

endfor

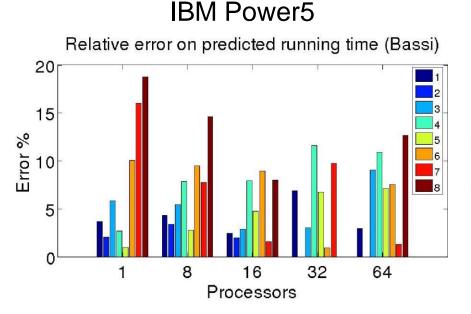
Endfor
```

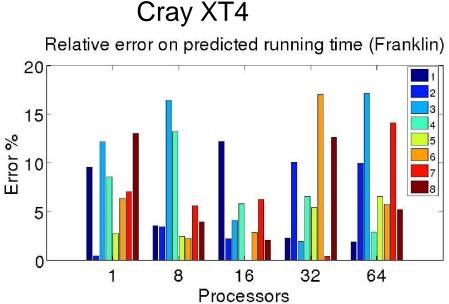
```
For all processor p that owns a block in row k do
  time[p] += memory_update (p, stack)
endfo
```

#### **Validation**



- 8 medium sized matrices from Univ. of Florida collection
- IBM Power5: 1.9 GHz, 8 CPUs/node
  - Average absolute prediction error 6.1%
- Cray XT4: 2.3 GHz, 4 cores/node
  - Average absolute prediction error 6.6%





# **Prototyping new algorithms**

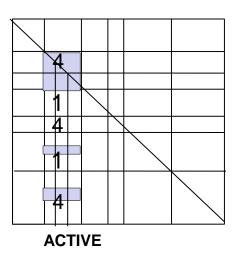


- Latency-reducing panel factorization
- Sparse Cholesky

## Latency-reducing panel factorization



- Panel factorization often on the critical path For each column within panel:
  - Scale column
  - Rank-1 update for rest of columns
- Two approaches
  - 1) Broadcast row for each rank-1 update
  - 2) Asynchronous Isend/Irecv



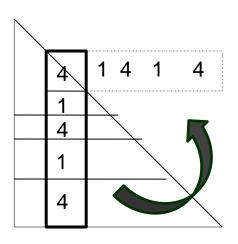
- Simulation shows 2) has more messages but fewer synchronizations, more parallelism
- Implementation of 2) led to 25% speedup @ 64 procs

### **New design: sparse Cholesky**



- Use the same data layout/mapping as in SuperLU\_DIST
  - Block column of L, block row of U on each processor
- Store only half of the matrix; half operations
  - No need for block row, nor upper triangular update
- Simple strategy
  - Block column of L is aggregated and replicated on the column processors
- Advantage: no need to change sparse data structures
- Disadvantages
  - Larger communication volume
  - Synch. of procs along each block column

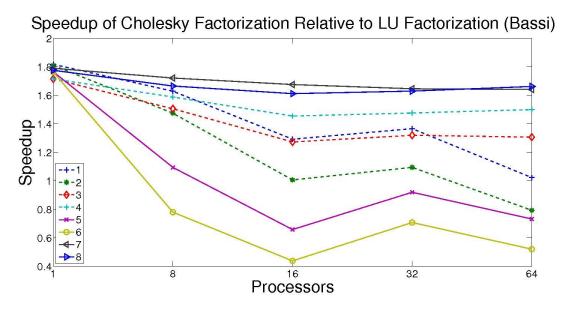
0	1	2
3	4	5



## Simulated results of sparse Cholesky



- Predicted that collective communication becomes major scalability bottleneck
- IBM Power5: Cholesky vs. LU, 8 matrices



- Future design: use truly block-oriented data format
  - Minimum comm. volume; no synch.
  - Comm. pattern not restricted within processor row

#### **Conclusions**



- Simulation-based performance modeling is very useful
  - Model complex applications that are input-dependent
    - Sparse LU: prediction errors mostly within 15%, average under 7%
  - Enable rapid prototyping of new algorithms
  - Evaluate new HPC system design
- Future work
  - Model resource contentions: memory, network